Mechanics of Advanced Composite Structures 10 (2023) 11 – 20

Semnan University

Mechanics of Advanced Composite Structures

journal homepage: http://MACS.journals.semnan.ac.ir

Springback Prediction of Sandwich Panel Using Machine Learning Methods

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KEYWORDS

Sandwich panel;
Springback;
Bending;
Numerical simulation;
Machine learning.

ABSTRACT

The purpose of this paper is to obtain a model that quickly predicts springback in the three-point bending process of steel / PUR / steel sandwich panels. Firstly, based on the finite element simulation, the springback behavior for different punch radius, length between supports, and foam thickness is established. The results obtained by the finite element analysis show a satisfactory agreement with the experimental results. Secondly, three machine learning approaches are applied, including linear regression (LR), artificial neural network (ANN), and support vector machine (SVM) in order to predict the springback of sandwich panels in the three-point bending process. The performance of these approaches is investigated by using some statistical tools like mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). The obtained results show that the ANN approach is the best model for predicting the springback of sandwich panels when considering accuracy.

1. Introduction

Sandwich panels are widely used in a variety of industrial products, such as aerospace, shipbuilding, external and internal walls of industrial buildings and automobiles; this is due to their lightweight, thermal and acoustic insulation and vibration reduction [1-4]. Sandwich structures are generally formed by two faces with high flexural rigidity and a core with lower performance [5-8]. In many cases, the face sheet is thin and rigid. Several types of face sheets are made from metal [9], composite structures [10], thermoplastic sheets [11], or wood. The core can be made of balsa wood, structural foam [10], or honeycomb [6]. Accurate modeling of deformations including springback is one of the most important issues in the industrial setting. In material forming, the quantitative evaluation of the springback phenomenon is very important.

The difference between the mechanical behavior of the face sheet and the foam core complicates the bending and the springback behavior of the sandwich panels. In order to improve the geometrical accuracy of the formed panels, proper selections of bending parameters are very significant. Some factors have considerable effects on springback, such as the sandwich geometry, the mechanical properties, and the process parameters. Many researchers have proposed analytical models based on material properties and geometrical parameters to predict springback [12-14]. Mohamadi et al. [12] suggested an analytical model for predicting the springback of sandwich panels composed of aluminum faces sheet and polypropylene foam core in a flexural test. They assumed that the maximum bending moment is located in the contact zone punch panel. They established the idea that the springback depends on the wrap around the punch which is estimated by an iterative method. Liu et al [13] developed an analytical model to obtain the springback angle in the air bending process of sandwich panels (aluminum-polymer). Their suggested model is primarily based on the analysis of the strain and stress distributions of the face sheets and the core materials. Recently, a semi-empirical method is proposed by Ouled Ahmed et al. [14] based on mechanical parameters and calibrated from experimental results (load-displacement) in the bending process. They found out that there is

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DOI: 10.22075/macs.2022.25933.1377
Received 2022-04-20; Received in revised form 2022-08-22; Accepted 2022-10-03.

a good agreement between the proposed semi-empirical model and the experimental data. Jian Wang et al [15] analyzed the influence of the fiber direction, temperature, and metal thickness ratio on the springback characteristics of the CFRP/Al laminates in different fiber directions through three-point and stamping bending of the laminates. They established that the springback rate varies by approximately 30% between room temperature and 150 °C.

The bending process and the springback prediction experiments are both time-consuming and expensive. The development of theoretical models for springback is also difficult due to the complexity of the panel bending process. Therefore, the finite element method (FEM) could be a helpful tool to predict springback. Most of the previous studies [16-20] have focused on the effects of the numerical parameters such as the number of integration points, the size element, and the contact algorithms on the springback prediction. More recently, Solfronk et al. [21] have investigated the effect of the computational model and the deformation mesh element strategy on the springback prediction of the sandwich panels in the U-bending process.

In addition, response surface methodology (RSM) is nowadays an important research topic since the industrial interest in cost and time reduction is always increasing. Few works of literature are available for the prediction of springback in the bending test of sandwich panels using RSM. Ouled Ahmed et al. [22] applied the RSM technique to predict the springback of steel/polyurethane/steel sandwich panels in a three-point bending process. They considered punch radius, length between supports, and thickness of foam core as inputs. Recently, methods of Machine Learning have been used for predicting springback in the sheet metal forming process. Vasudevan et al. [23] compared the RSM and the artificial neural network (ANN) approaches to predict springback in air bending of electronically-galvanized steel sheets. The ANN model was based on a multi-layer feed-forward topology and trained with a Levenberg-Marquardt (LM) back-propagation algorithm. They found that the performance of the ANN model was better than the RSM models. Fei Han et al. [24] proposed a model combining FEM and the ANN approach to obtain a relationship between springback and processing parameters. Pathak et al. [25] used FEM and ANN techniques to predict the springback of the metal sheet during the air-bending process. The input parameters were the sheet thickness and the support radius. They observed that the ANN provides fairly accurate predictions of the formed metal sheet. Stefanos et al. [26] proposed a novel ANN, based on Bayesian regularized back-propagation networks, for the prediction of springback in sheet metal forming processes. They reported that the obtained results were in good agreement with the FEM prediction.

In addition to the ANN approach, serial new machine learning techniques have emerged such as linear regression (LR) and support vector machine (SVM). However, there is a lack of springback prediction when using the SVM. Kumar et al. [27] applied the SVM technique combined with the FEM to predict the springback in V-bending. Teng et al. [28] employed the SVM to predict springback in the three-dimensional stretch bending process. They found out that the springback prediction was more accurate than the ANN method.

Based on the present literature, no studies have dealt with springback predictions of sandwich panels using machine learning. This study consists of using the LR, the ANN, and the SVM methods to predict the springback of sandwich panels in the three-point bending process. The performances of these models are investigated and compared with FEM results.

2. Test Material

The two face sheets (for each face thickness of 0.5 mm) were made of galvanized steel. The core was obtained from rigid polyurethane foam (PUR) with a density of 40 kg/m^3. The steel/ PUR/ steel sandwich panels were obtained by an injection method. A screw-driven MTS Insight universal testing machine, equipped with a 200 kN load cell, was used to perform compression and tensile tests of the foam core and the face sheet respectively. The obtained mechanical properties are given in Table1 [14].

Table 1. Mechanical properties of the components of the sandwich panel

	Steel face sheet	Polyurethane foam core
Density ρ [kg/m3]	7800	40
Yield stress σ_0 [MPa]	440	0.41
Young's modulus E [MPa]	200000	3.31
Poisson's ratio ν	0.3	0.4
Ultimate tensile strength Rm [MPa]	453	0.53

Steel faces sheet with a thickness of 0.5 mm and polyurethane foam with a thickness of 40 mm were used for the preparation of sandwich panels. All sandwich panels were 500 mm long, 50 mm wide, and between 40 mm and 60 mm thick (Fig. 1).

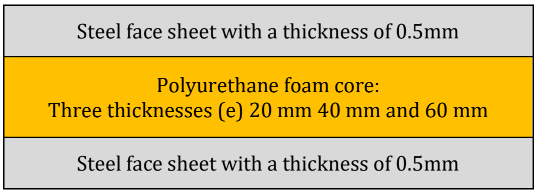

Fig. 1. Steel/ PUR/ steel sandwich panel.

Quasi-Static three-point bending tests, according to the standard ASTM D 790, were conducted with the MTS Insight testing machine to acquire the load-displacement curves. These tests were performed by using the following process parameters: punch radii of 82 mm; length between supports of 200 mm and support radius of 10 mm. The punch stroke was 30 mm and the displacement rate was 3 mm/min.

3. Finite Element Analysis

3.1. Bending Simulation

Implicit finite element analysis was used to simulate the three-point bending followed by the springback of steel/ PUR/ steel sandwich panels using the ABAQUS 6.14 software package. Due to the material symmetry, only half of the geometry was modeled. The 4-node bilinear plane strain quadrilateral, the reduced integration, and the hourglass control element (CPE4R) were used.

Frictional effects were taken into account by means of Coulomb's law. The friction coefficient of 0.1 was set for interactions between punch and support contact surfaces with the sandwich panel similar to the value used by Schwarze et al. [29]. Several simulations were conducted and proved that there was no significant effect of the friction coefficient on the numerical results explained by the fact that the contact zones tools/panels were small (punctual contact in 2D space). In order to get more accurate results, the experimental data of the tensile and the compressive tests were used as input data in the finite element software Abaqus.

Table 1 summarizes the identified mechanical properties of the face sheet and the foam core.

Punch and die were modeled as analytical rigid bodies. It is well established that the number of elements through thickness has great importance on the accuracy of the finite element simulations, particularly in bending processes as recommended by Meinders et al. [30] and Chatti et al. [31].

Different simulations were done using an increasing number of elements through the panel thickness using the same number of elements for each layer. It can be seen from Fig. 2 that as the elements' number increases, the punch load converges to a certain value and it seems that 60 elements (20 elements for each layer) were sufficient to obtain an accurate result. In addition, the panel was sufficiently refined in the vicinity of the tool's contacts in order to ensure more accurate results. For all the FEM simulations, 1600 elements for the foam core and 3200 elements for each face sheet were used. Three-point bending tests were executed by changing the parameters of the following process parameters: three thicknesses (e) of 20 mm 40 mm and 60 mm, three punch radii (Rp) of 82, 102, and 115 mm, and three lengths between supports (L) of 200, 250 and 300 mm.

Firstly, the punch moves downwards in order to bend the panel reaching a full punch stroke Yp of 30 mm. In the second step, the tools are removed and springback ΔY_p can be predicted by measuring the difference between the deflection of the sandwich panel before and after removing the punch as shown in Fig. 3.

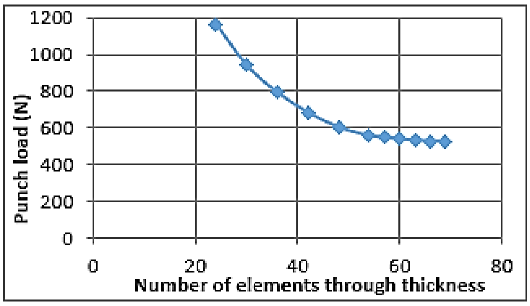

Fig. 2. Punch load vs. element number through thickness (Yp=30 mm; L= 200 mm; Rp=82mm; e=40mm).

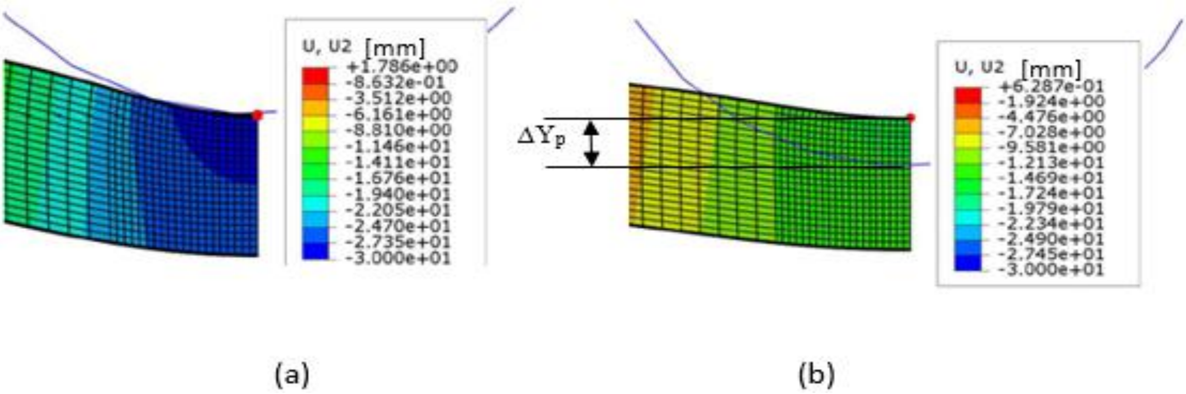

Fig. 3. Bending simulation; (a) before unloading, (b) after unloading (springback).

3.2. Validation of the FEM Model

In Fig. 4, the punch load vs. the punch displacement obtained from the experiment and numerical results is plotted. The results obtained by the finite element analysis show a satisfactory agreement with experimental results in terms of overall trends.

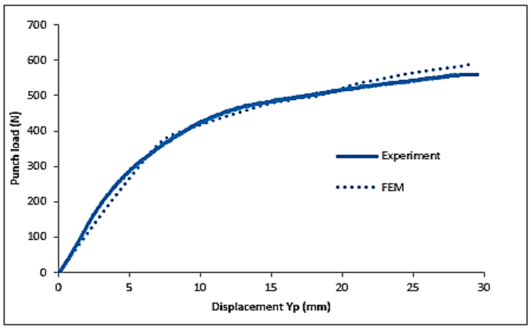

Fig. 4. Punch load vs. the punch displacement obtained from experimental and numerical results (L= 200 mm; Rp=82mm; e=40mm).

Table 2 gives some numerical and experimental results of springback [14]. It can be inferred that the obtained results are acceptable.

Table 2. Comparison of numerical and experimental values of springback

e (mm)	L (mm)	Rp (mm)	ΔYp EXP (mm)	ΔYp FEM (mm)
40	250	82	15	12.23
40	300	82	16	14.01
40	300	102	17	14.25
40	300	115	18	14.59
60	300	82	14	12.5

3.3. Springback Prediction

In this study, several sheet thicknesses, length between supports, and punch radii are considered. The results obtained by the finite element analysis of the springback of sandwich panels in the three-point bending process are shown in Fig. 5. This figure clearly shows that the amount of springback increases with increasing distance between the supports. Figure 5 also shows that mostly when the springback slightly increases, the punch radius increases too. However, it can be seen that the springback decreases as the core thickness increases.

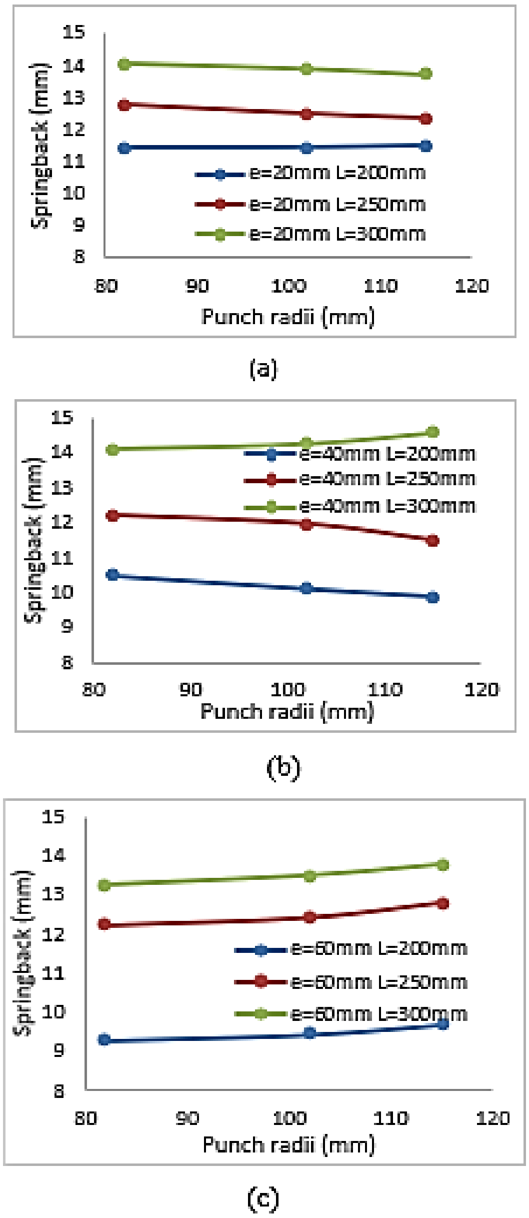

Fig. 5. Effect of the foam thickness, length between supports and punch radii on springback; a) e=20mm; b) e=40mm; c) e=60mm.

4. Methodology of Machine Learning

The machine learning approach is used to update the FEM for springback prediction in the three-point bending test. Three machine learning models are considered including linear regression, artificial neural network, and support vector regression. As displayed in Fig. 6, the attributes (inputs) for each case of sandwich panels are the punch radius, the distance between supports, the core thickness, and the results of the FEM simulation.

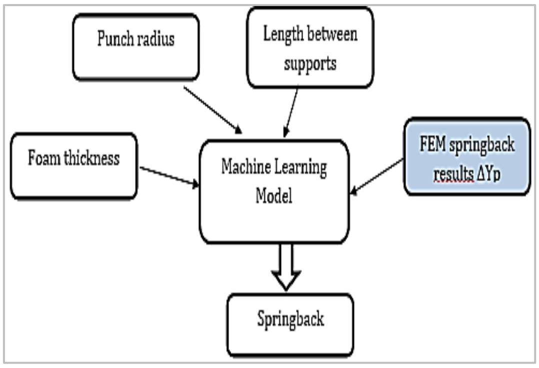

Fig. 6. Machine learning Diagram

4.1. Linear Regression

The regression approach is one of the most common statistical techniques [7, 10]. Regression analysis is a method of modeling a functional relationship between two or more variables. The purpose of the regression methodology is to use independent variables (inputs) that are known to provide the only dependent variables (response). The model considered is the linear regression (LR) is a linear equation expressed by:

$$Y = \alpha_0 + \sum_{i=1}^{n} \alpha_i X_i \tag{1}$$

where Y denotes the dependent variable (response), n is the number of input factors, αi are the regression coefficients and X_i's are the independent variables (inputs). For the springback response, the inputs will be the punch radius, the distance between supports, and the core thickness. By using the Rapidminer software, the springback ΔY_p is obtained:

$$\Delta Y_P = 4.199 - 0.020 \times e + 0.035 \times L - 0.000 \times R_P \tag{2}$$

Figure 7 presents the comparison between the results obtained by the FEM and by the LR approach. It is clear that this relationship is almost along a line representing the capacity of this model to predict springback. The RMSE and R^2 for the LR are 0.823 and 0.906 respectively.

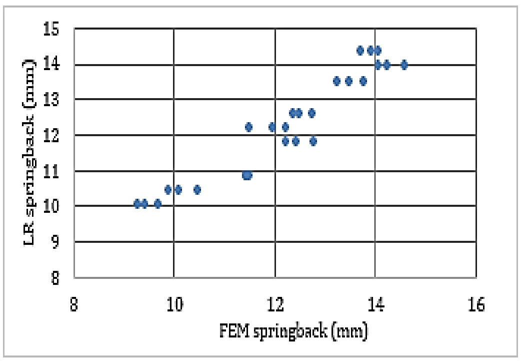

Fig. 7. Linear regression predicted output results vs. numerical simulation results

4.2. Artificial Neural Networks

Artificial neural networks have emerged as a new branch of computing that leads to the resolution of problems encountered in the modeling and optimization of several processes. It is one of the most useful techniques for resolving engineering design issues and reducing errors in experimental data. The ANN method was inspired by both human biological neural network systems and mathematical theories of information learning, processing, and controlling.

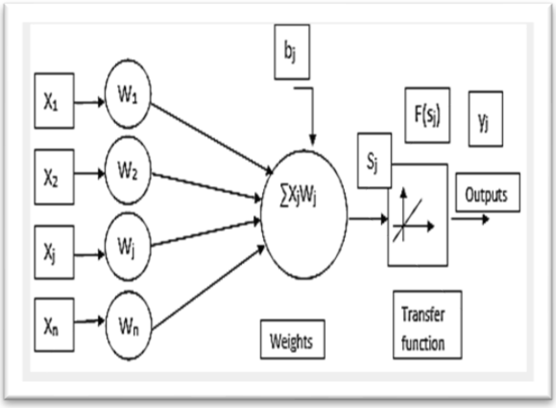

Fig. 8. Basic structure of an artificial neuron

A multilayer neural network structure consists of an input layer, hidden layers, and an output layer. Figure 8 shows the basic structure of an ANN. The input layers (X_1,...,X_n) are the layers that receive input data and then transfer it to the hidden layer which will be used as training data for the ANN. The weighted values W_i are transmitted to the neuron where they are changed by the threshold function, like the sigmoid function. The output layer obtains all the responses from the hidden layer and transfers a corresponding output.

The output of any neuron is expressed as follows:

$$S_i = \sum_{j=1}^{n} x_j w_{ij} + b_j \tag{3}$$

where n is the input number, x_j denotes the value received from the earlier neuron, w_{ij} is the weight between the i and j neurons and b_j denotes the neuron bias. The output of the neuron is expressed by:

$$y_i = f(S_i) \tag{4}$$

where f is the transfer function.

The network has been trained using the Levenberg-Marquardt back-propagation algorithm. This algorithm is displayed in Fig. 9 and is specially designed to reduce the sum of squared error's function.

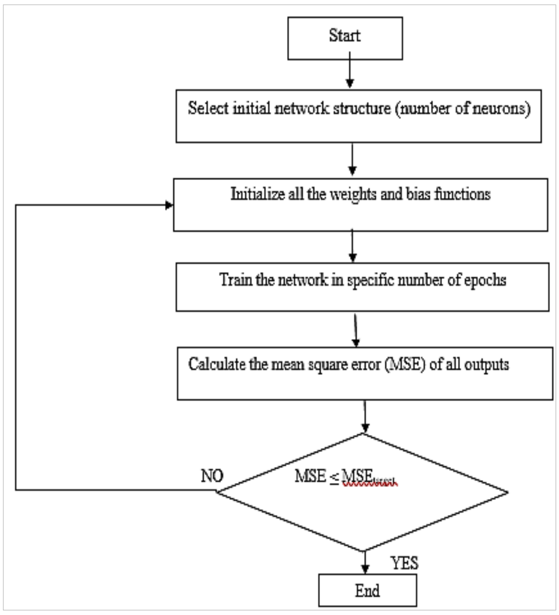

Fig. 9. Procedure for identifying the optimal ANN architect

The equation for updating weights and bias for each node of the neural is expressed by:

$$w_{ij}^{z+1} = w_{ij}^{z} + \Delta w_{ij}^{z+1} \quad (5)$$

Based on the LM back-propagation algorithm, the weight change can be assumed by:

$$\Delta w_{ij}^{z+1} = \left[J^T J + \mu I \right]^{-1} J^T e + \alpha \left(w_{ij}^{z} - w_{ij}^{z-1} \right) \quad (6)$$

where z denotes the step of learning, Δw_{ij}^{z+1} is the increment of the weight, J is the Jacobean matrix containing the first derivative of the network error related to the weight and bias, μ denotes the adaptive learning parameter, I is the identity matrix, the vector e is the network errors vector and α denotes the momentum term.

The mean-square-error (MSE) of all outputs can be assumed as follows:

$$MSE = \frac{1}{n} \sum_{j=1}^{n} (t_j - a_j)^2 \quad (7)$$

where n is the number of sets containing the input and output data, a_j 's are the output based on the input values, and t_j 's are the corresponding predicted output values.

Various networks have been studied considering different scenarios where not only the number of hidden layers is different, but also the number of neurons in each hidden layer is different, too. All possible ANN cases have been consulted via MATLAB script, and finally, the one with the smallest generalization error has been selected as the representative one.

In this study, the number of neurons in the hidden layer is modified and the MSE is evaluated as given in Table 3. As soon as the MSE of the training data reaches the target value, the training is stopped and the weights and biases are saved. After several trials, the number of neurons with minimal MSE is selected for the hidden layer to be 14. The designed architecture will be 3-14-1.

Table 3. Effect of the number of neurons on the MSE and R^2

N°neurons	MSE	R^2
10	0.436	0.774
11	0.987	0.321
12	0.476	0.908
13	1.691	0.608
14	0.066	0.990
15	0.648	0.794
16	1.425	0.440

Figure 10 presents the numerical prediction and the corresponding ANN predictions of springback. Linear regression between all the values of the springback shows that all the points are dispersed around a line with a slope close to 1.

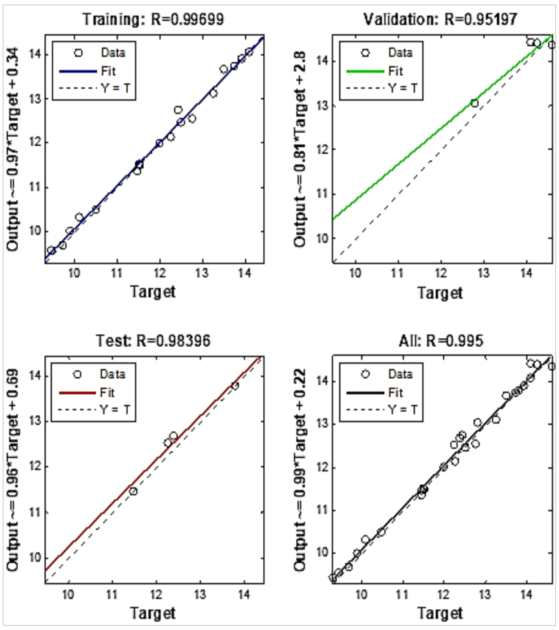

Fig. 10. Regression of predicted neural network output result and numerical simulation target value

4.3. Support Vector Machine

Recently, the support vector machine approach has been used to predict the springback of metal sheets in the bending process. The principle of the SVM is to map the non-linear problems in the original space to the linear problems in high-dimensional feature space. This non-linear transformation is obtained by defining the appropriate kernel (algorithm) function.

The objective of the SVM modeling is to obtain the linear function expressed by:

$$f(x) = \langle w; \varphi_i(x_i) \rangle + b \quad (8)$$

where $\langle\ \rangle$ denotes scalar product, $\varphi_i(x_i)$ is a non-linear mapping vector of the input vector x_i, *w* is the weight vector and *b* is a bias constant.

For a given training sample of n data points $\{x_i, y_i\}$; *i*=1,...*n*, the risk function, to be minimized, is expressed by:

$$R(C) = \frac{1}{2}\|w\|^2 + \frac{C}{n}\sum_{i,j=1}^{n} L_\varepsilon(f(x_i), y_i) \quad (9)$$

where *C* is a regularized constant, $\|w\|$ is the norm of the weight vector w, $L_\varepsilon(f(x_i), y_i)$ is called the ε insensitive loss function [32] and assumed by the following equation:

$$L_\varepsilon(f(x_i), y_j) = \begin{cases} |(f(x_i) - y_i)| - \varepsilon & |(f(x_i) - y_i) \geq \varepsilon| \\ 0 & otherwise \end{cases} \quad (10)$$

Notice that the regularization constant C determines the barter between the training error and $\|w\|$.

In order to obtain an acceptable degree of error, the deviation variables ξ_i and ξ_i^* have been used as shown in Fig. 11. These variables present the distance from the actual value to the corresponding limit of ε. The goal of the SVM is to reduce ξ_i, ξ_i^* and $\|w\|^2$ as expressed by:

$$Min \quad R(w, \xi_i^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (11)$$

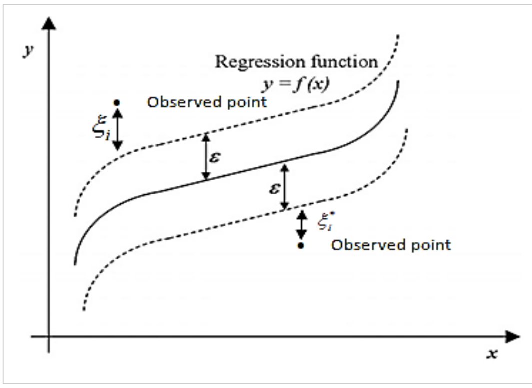

Fig. 11. Non-linear regression with ε insensitive band in the SVM model [27]

Lagrangian multipliers have been used to convert the above optimization equation (Eq.11) to a quadratic programming problem. The solution to this problem can be expressed by:

$$f(x) = \sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b \quad (12)$$

with the constraints

$$\sum_{i=1}^{n} \alpha_i^* = \sum_{i=1}^{n} \alpha_i$$

$$0 \leq \alpha_i \leq C \qquad i = 1, \ldots, n$$

$$0 \leq \alpha_i^* \leq C \qquad i = 1, \ldots, n$$

where α_i and α_i^* are the Lagrange multipliers, $K(x_i, x_j)$ is a kernel function whose values are the inner product of two vectors x_i and x_j in the feature spaces $\phi(x_i)$ and $\phi(x_j)$ which satisfies Mercer's condition. The kernel function is expressed by:

$$K(x_i, x_j) = \phi(x_i).\phi(x_j) \quad (13)$$

which is frequently used as a polynomial (Eq. 14) or radial (Eq. 15) function:

$$K(x_i, x_j) = (x_i..x_j + 1)^d \quad (14)$$

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (15)$$

where d is the degree of a polynomial function and σ is the variance also called hyperparameter.

Based on 27 cases analyzed using the finite element method, an SVM has been trained. Punch radius, length between supports, and foam thickness have been selected as the primary inputs; where the springback is used as the output. A computer program has been performed under the Rapidminer script. Training of the SVM has been performed using the two kernel functions (radial and polynomial).

To determine a more accurate combination of these functions' parameters, various combinations are tested. Tables 4 and 5 summarize the main parameters tested for each Kernel function.

Table 4. Parameters of the polynomial kernel

Degree of kernel function d	1(linear) 2(quadratic) 3 (cubic)
Regularization parameter C	1 10 20 30 40 50 60 70 80 90 100

Table 5. Parameters of radial kernel

Gamma in kernel function $\gamma = \frac{1}{\sigma}$	0.1 0.2 0.3 0.4 0.5 0 .6 0.7 0.8 0.9 1 2 3 4 5 6 7 8 9 10 20 30 40 50
Regularization parameter C	1 10 20 30 40 50 60 70 80 90 100

The predicted performance of the SVM models has been evaluated using some statistical properties such as MAE, RMSE, and R^2. Tables 6 and 7 summarize the best combinations of radial and polynomial kernel functions' models and the corresponding performances. The results from the model training reveal that the cubic kernel function for predicting springback is the best polynomial model. However, the radial model is the best SVM.

Table 6. Best parameter combinations of the polynomial kernel

Kernel type	C	MAE	RMSE	R^2
Linear	80	0.479	0.612	0.901
Quadratic	10	1.360	1.607	0.493
Cubic	50	0.509	0.717	0.929

Table 7. Best parameters combinations of radial kernel

GAMMA	C	ε	MAE	RMSE	R^2
0.7	10	0.01	0.454	0.541	0.962

The scatter plot of the springback' results obtained by numerical simulation and the values predicted by the four SVM models are presented in Fig. 12. The predicted values of cubic and radial models are narrowly distributed on both sides of the line y = x. As mentioned above, these two models predict the springback more accurately than the others.

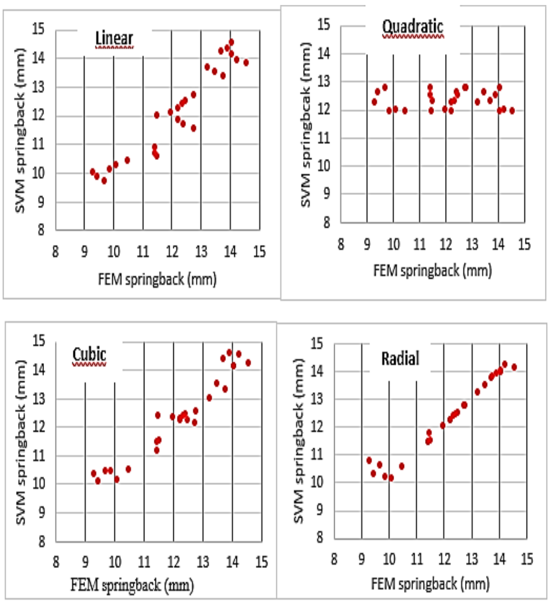

Fig. 12. Scatter plots of the SVM springback vs. the FEM springback.

Figure 13 gives the comparison between the springback obtained by the FEM and by the four SVM models. It can be concluded once more that the radial kernel function gives the best results when compared with the FEM results.

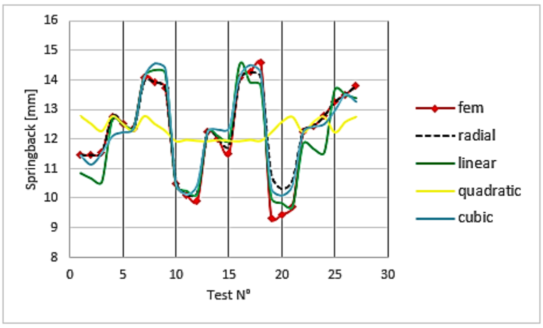

Fig. 13. Comparison between the four SVM models and the FEM.

5. Discussion

The results obtained with the LR, the ANN, and the SVM methods on the springback prediction are compared and discussed. From the obtained results, the following conclusions are drawn. The LR clearly shows that the distance between the supports and the thickness of the foam is the most influential parameters for the springback of the sandwich panel. However, it turns out that the punch radius is not a significant parameter.

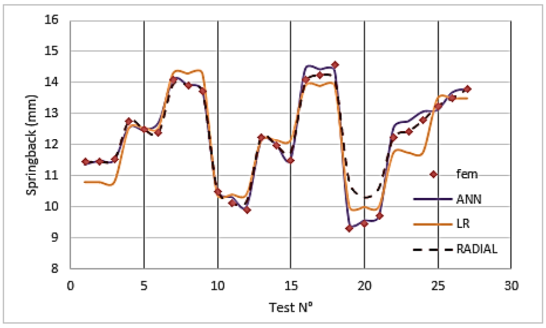

Fig. 14. Comparison between the three machine learning models, (LR), (ANN), and (SVM).

The ANN approach based on the LM back-propagation algorithms was used as a learning algorithm in the multilayered feed-forward networks. An increased number of neurons from 10 to 16 in a single hidden layer were considered. For the comparison, some statistical methods such as R^2 and MSE values have been used. It has been found that the LM algorithm with 14 neurons gives the best results.

The SVM using four kernel functions (radial, linear, quadratic, and cubic) reveals that the radial method is the best one for predicting springback in the training data. Figure 14 gives a comparison between the numerical results of the springback and the predicted values obtained by the three machine learning models. This figure shows that the ANN model is the best accurate model for predicting springback when compared with the FEM.

6. Conclusion

This paper consists of predicting the springback of the sandwich panel under three-point bending process by using several approaches of machine learning, including linear regression, artificial neural network and support vector machine. By using FEM, the predicted springback has been used as input to the three machine learning models. The obtained results show that the ANN approach is found to be the best approach for predicting springback.

Conflicts of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/ or publication of this article.

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